QL-CONST1: an expert system for quality level prediction in concrete structures

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In recent years, an ever-increasing effort has been devoted to the research, development and marketing of expert systems in a great number of specific fields of human knowledge although few of them have reached a truly production status.

Knowledge engineering, which is closely related to expert systems, will have very important impact in those areas of human activities where knowledge provides a powerful tool for solving relevant problems. Thus, it is possible to predict two beneficial effects[1]: firstly, an increase in knowledge based systems development for reproducing and applying human knowledge and secondly, as an inevitable side effect, knowledge engineering will accelerate the development, clarification and expansion of human knowledge itself.

Figure 1 illustrates a typical expert system with its basic modules.

Table 1 contains a summary of the most relevant problems which are susceptible to knowledge engineering technology and their identification keywords.

In some fields of human knowledge (for example, medicine, law, mathematics and management) a considerable number of expert systems have been developed to help specialists[1,2,4–6]. However, in structural engineering, the number of expert systems is not so large. In the following paragraphs we briefly review some of them in order to appraise some of the existing possibilities.

SPERIL-II,[7] developed at Purdue University, evaluates the general safety and damageability of existing structures by analysing inspection data and instrumental records of the structural response (displacements, accelerations, etc.) as a consequence of earthquake loading. The system has a predicated logic rules knowledge base and uses both forward and backward chaining combined with certainty factors for its reasoning process. It was written in a dialect of Prolog.

SACON[8], developed at Stanford University, determines particular ways and strategies for analysing structural engineering problems. The system is coupled with MARC (Finite Element Method code). It is a rule based system with backward chaining for the inference process.

CONPHYDE[9], developed at Carnegie-Mellon University, selects appropriate estimation methods of physical properties to help chemical engineers. Once the system has been given information about concentration, pressure

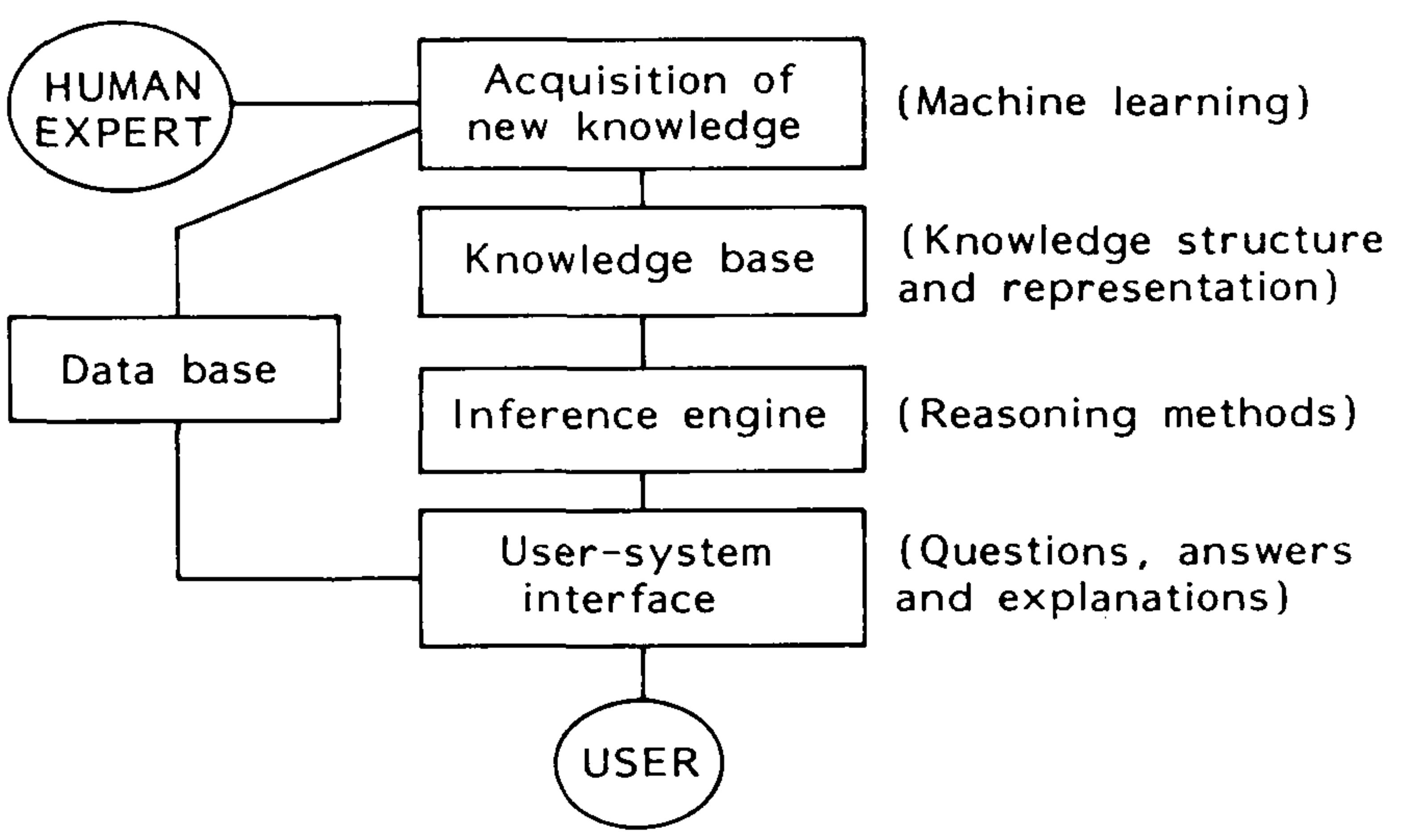

Fig 1 A typical expert system

Table 1 Knowledge engineering influence areas (from reference 2)

Category	Problem addressed
Interpretation	Inferring situation descriptions from sensor data
Prediction	Inferring likely consequences of given situations
Diagnosis	Inferring system malfunctions from observations
Design	Configuring objects under constraints
Planning	Design actions
Monitoring	Comparing observations to plan vulnerabilities
Debugging	Prescribing remedies for malfunctions
Repair	Executing a plan to administer a prescribed remedy
Instruction	Diagnosing, debugging and repairing student behaviour
Control	Interpreting, predicting, repairing and monitoring system behaviours

and temperature conditions from a specific vapour–liquid combination, it starts performing a simulation process. The system works with certainty factors and Bayesian inference to estimate the probabilities associated with input data.

REACTOR[10], also developed at Stanford University, assists nuclear reactor operators in the diagnosis and treatment of nuclear reactor accidents. When the system detects any malfunction, it evaluates the resultant situation and recommends the appropriate action by using its knowledge about the expected reactor response in the presence of known accident conditions. The system uses both forward and backward chaining. It was written in LISP.

Another expert system, also based on Bayesian inference, is PROSPECTOR[11], developed by SRI International. This powerful expert system helps geologists in their exploration for mineral deposits by assessing the potential for the existence of such deposits as porphyry copper, massive sulphide, and porphyry molybdenum. The system works by using rule based knowledge and certainty factors, together with Bayesian inference, to determine the probabilities associated with input data. It was written in INTERLISP and has reached the production prototype stage.

The work described here is devoted to the generation of a knowledge base for quality level prediction in concrete structures and its implementation on a Bayesian type expert system, QL-CONST1 (Quality Level prediction in CONcrete STructures, version 1). Our aims are twofold: firstly to reinforce the non-extended idea that expert systems will be a useful and invaluable tool for assisting structural engineers in making decisions. Secondly, as a long-term aim, we intend that more advanced versions of QL-CONST will be able to work as a 'tutorial', i.e. to be able to guide and teach structural engineers (and, of course, engineering students) to assimilate specific knowledge quickly by interacting with an expert system.

The Bayesian approach for probabilistic phenomena

The well known Bayes Theorem has singular importance in processes normally involving probabilistic knowledge, such as engineering design, damage assessment and quality level prediction. In these cases, information which must be included in the inference process is available from

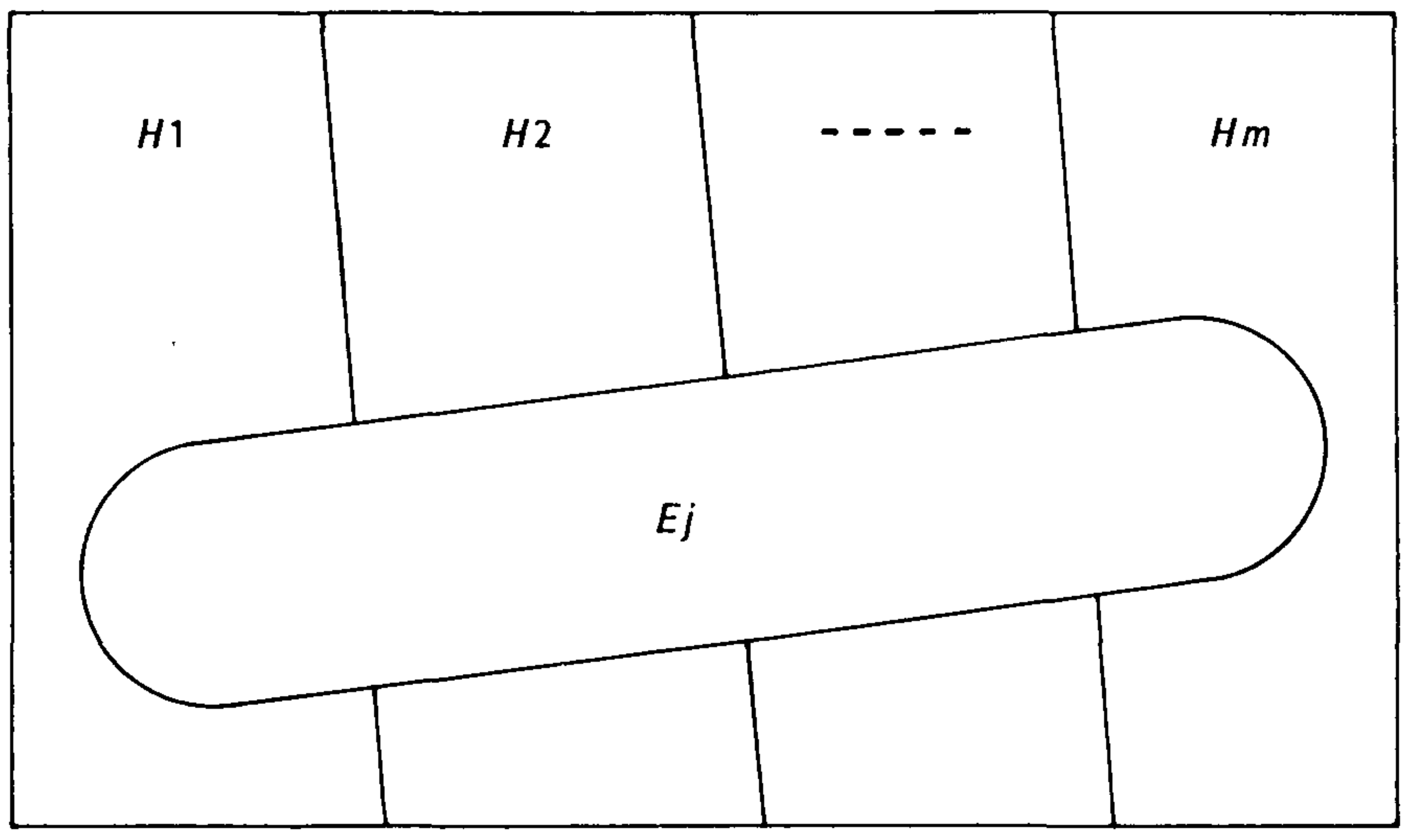

Fig 2 Universe of mutually exclusive hypotheses

various sources: for example, the engineer's experience (subjective), visual inspection and experimental tests, which produce a great amount of statistical data. Moreover, engineers may also have some additional experience in classifying events which could occur more frequently than others and their importance in the context of engineering design.

We will briefly review the basic ideas and formulae inherent in the Bayes Theorem, as follows. Let U be the universe comprising a set of m mutually exclusive events H_i; let E_j be another event belonging to U.

The conditional probability for the presence of event E_j assuming that event H_i has occurred is:

$$P(H_i:E_j)=\frac{P(H_i \ \& \ E_j)}{P(E_j)} \tag{1}$$

where

$P(H_i \ \& \ E_j)$ = probability for the occurrence of both events simultaneously.

From equation (1) we can write:

$$P(H_i \ \& \ E_j)=P(H_i:E_j)\times P(E_j)$$

$$P(E_j \ \& \ H_i)=P(E_j:H_i)\times P(H_i) \tag{2}$$

Therefore

$$P(H_i:E_j)\times P(E_j)=P(E_j:H_i)\times P(H_i) \tag{3}$$

Now, Bayes' Theorem could be expressed as:

$$P(H_i:E_j)=\frac{P(E_j:H_i)\times P(H_i)}{P(E_j)} \tag{4}$$

If the H_i are mutually exclusive and collectively exhaustive, then the Total Probability Theorem may be used to expand $P(E_j)$ yielding

$$P(H_i:E_j)=\frac{P(E_j:H_i)\times P(H_i)}{\sum_k P(E_j:H_k)\times P(H_k)} \tag{5}$$

In our case, H_i should be interpreted as a hypothesis, whereas E_j represents some piece of evidence. In light of this, the various terms in equation (5) have the following interpretation: $P(H_i)$ = probability *a priori* for the occurrence of hypothesis H_i, prior to the availability of any evidence $E_j P(H_i:E_j)$ = probability *a posteriori* for the occurrence of H_i, updated by knowing the presence of the evidence E_j and $P(E_j:H_i)$ = conditional probability for the presence of evidence E_j, assuming that H_i has occurred. The set of E_j could be of various types, including: visual inspection, experimental outcomes, an expert's knowledge and belief, etc.

Probability knowledge base for QL-CONST1

The expert system described here works under the assumption of probabilistic knowledge with Bayesian inference. Thus, the knowledge base (KB) is constructed upon *a priori* and conditional probabilities with the assistance of human experts in structural engineering and safety of structures. It is usually accepted[1,2,3] that this step in expert systems development is probably the most difficult, due to the fact that the knowledge engineer must elicit a human expert's knowledge and encode it into numerical values of probability. However, with some effort, it is possible to do this and to obtain reasonably useful results, as can be seen later.

For discussion purposes we reproduce Bayes' formula[20]:

$$P(H_i:E_j)=\frac{P(E_j:H_i)\times P(H_i)}{P(E_j)} \tag{6}$$

In general, the term $P(E_j)$ is evaluated through the Total Probability Theorem (see equation (5) as:

$$P(E_j)=\sum_k P(E_j:H_k)\times P(H_k) \tag{7}$$

However, in our case, we will evaluate this term through a subset simplified formula, which is essentially a subset of equation (7):

$$P(E_j)=P(E_j:H_i)\times P(H_i)+P(E_j:\bar{H}_i)\times P(\bar{H}_i) \tag{8}$$

where the same definitions as for equation (5) apply, plus $P(\bar{H}_i)=1-P(H_i)=$ probability *a priori* for the non-occurrence of H_i and $P(E_j:\bar{H}_i)=$ probability for the presence of E_j, provided that H_i has not occurred.

When the *KB* is incomplete with respect to all possible hypotheses H_k (and their corresponding $P(E_j:H_k)$), then equation (8) is preferred to equation (7), because the latter could lead to an incorrect calculation of $P(E_j)$. Thus, substituting equation (8) into equation (6), Bayes' formula could be rewritten as:

$$P(H_i:E_j)=\frac{P(E_j:H_i)\times P(H_i)}{P(E_j:H_i)\times P(H_i)+P(E_j:\bar{H}_i)\times P(\bar{H}_i)} \tag{9}$$

If E_j does not occur (i.e., $\bar{E}_j$) we arrive at the complementary formula of equation (9):

$$P(H_i:\bar{E}_j)=\frac{P(\bar{E}_j:H_i)\times P(H_i)}{P(\bar{E}_j:H_i)\times P(H_i)+P(\bar{E}_j:\bar{H}_i)\times P(\bar{H}_i)} \tag{10}$$

In QL-CONST1 (version 1) three basic hypotheses are included: GOOD quality level; MEDIUM quality level; and POOR quality level. The hypotheses are codified in the KB in natural language to allow better understanding by someone dealing with any modification. They are held inside a file named Structural which is stored completely apart from control and inference process. Each hypothesis has associated with it a considerable number of evidences E_j and a set of probabilities which are: $P(H_i)$ for the hypothesis itself and $P(E_j:H_i)$ and $P(E_j:\bar{H}_i)$ for each of the evidences related to the hypothesis. Obviously, the number of hypotheses could be easily expanded for dealing with a more sophisticated gradation of the system reasoning and answers. This is being currently done for other more advanced versions of QL-CONST.

The evidences are codified into another file named Quality (also in natural language and clearly separate from the KB and inference process) organized in the form of a list of items. These are the questions that the system asks the user in order to incorporate *a posteriori* information for the inference process. The system always knows, at run time, which of the evidences affect each of the hypotheses and in what way.

Evidences were classified into several groups, depending upon their source, namely:

Visual inspection;
Control of materials;
On-site inspection of construction;
Project and building plans.

In general, all evidence affects all the hypotheses involved here, although this may not always be the case.

Description of expert system QL-CONST1

QL-CONST 1 is a small expert system written in Pascal, running on an HP-9836 micro-computer. QL-CONST1 performs its reasoning process through Bayesian inference. The final goal is to obtain the probability of occurrence for the likely hypothesis H_i by including and merging all the required evidences. The system works in a simple way, asking the user questions in order to incorporate new evidences (i.e. *a posteriori* information) into the reasoning and inference process. For the first time, the system assigns the given value $P(H_i)$ for all hypotheses to the variable $P(H_i:E_j)$ (The system permanently holds the $P(H_i)$ values in the KB). Now, these probability values are updated, using Bayes' Theorem (see equations 9 and 10), by asking about any new evidences (for instance, presence or absence of shear cracks). This process is repeated again and again, according to new evidences coming in, by simply using the last conditional probabilities $P(H_i:E_j)$ in place of *a priori* probabilities, $P(H_i)$, until the system reaches a reliable conclusion and announces it.

The sequence used by the system to ask its questions deserves some more attention. Before it asks anything, it has to compute a rule value[12,19], which works like a parameter to indicate which evidence produces the largest shifts on the hypotheses and, therefore, the next one to be requested. Once the system has found this evidence, it asks the user a question, inputs the corresponding answer and updates conditional probabilities for all hypotheses, as described above. This rule value is merely a parameter depending upon $P(E_j:H_i)$ and $P(E_j:\bar{H}_i)$. The system continually modifies its judgement about which question is the most relevant at the current state of the reasoning chain. In this sense, the system responds intelligently to the user's answers. This method is termed 'sideway chaining', because it is basically a function of the evidences instead of the hypotheses.

The way the user answers the system's questions is another topic of interest. In classical binary logic, events either occur or do not occur. This implies that answers for any requested evidence would be either true (1) or false (0). Nevertheless, in probabilistic processes (also in those governed by Fuzzy Logic Theory[13,14,21] knowledge is no longer either true or false, but has an associated degree of uncertainty[2,15,16]. Thus, when the system requests information about a particular evidence, for example, 'was there effective protection for materials against rain?', it becomes necessary to allow the user to reply with phrases such as 'I don't know' (absolute uncertainty) or 'more or less' (maybe 'yes' but not really sure).

To deal with such an uncertainty, QL-CONST1 accepts the user's answer in the form of a numerically graded scale comprising the integers from -5 to $+5$. Absolute certainty is represented by $+5$, impossibility by 5 and absolute uncertainty by zero. The answer 'more or less' yes could be equivalent to the number 2 for instance. In this way, the system performs a linear interpolation between the Bayes' formulae equations (9) and (10), to include the effect of user uncertainty. Other more advanced techniques for including uncertainty are beyond the scope of this work. The interested reader is referred to references 2,4,14,17,18 for further details.

The method of stopping the question–answer process is to assess if, at the current moment, some evidence exists (still to be requested) which would make the conditional probability of one hypothesis larger than the maximum conditional probability associated with any other hypothesis. If this condition is FALSE, the system has reached the most likely and reliable conclusion (hypothesis). It then announces it with its probability in terms of percentage, without asking more questions. If the previous condition is TRUE, the system continues asking questions and updating probability values until it reaches the value of FALSE for the stopping criterion.

Assessment and reliability of expert system behaviour

This section is devoted to the validation of the previously described expert system. When evaluating the performance of an expert system a wide variety of questions arise. In this case, owing to the relative simplicity of the reasoning process, discussion is restricted to a few, namely:

Does the knowledge base adequately represent the problem under consideration, i.e., are the inference rules correctly formulated and embodied into the knowledge base?

Do the test examples cover the knowledge domain and assess the system's recognition of the boundaries for the limit cases?

Does the system's enquiring process follow a natural and reasonable sequence similar to that which an expert might follow? An illogical sequence for requesting information may result in diminished user confidence in the system.

The knowledge base developed here was extensively tested and, consequently, modified taking into consideration the suggestions from many human experts. Although the present version of the KB is a prototype and correspondingly small, it is able to cover a wide variety of structural situations. With regard to the second question formulated above, some test examples comprising special and critical situations were considered, giving satisfactory results. Two of them will be shown and discussed further.

The third question also deserves special attention and should be treated carefully. In order to achieve the goal proposed above, i.e. some degree of optimization and rationality of the sequence of computer questions, the rule value was modified and optimized together with a selective refinement of the probability values. This combined approach leads to a sequence of questions which are more efficient and closer to human behaviour. Accordingly, the system reaches its conclusion by asking the user fewer questions, and shows a faster convergence to the required prediction. The dialogue sequences for specific predefined structural situations will be displayed in order to show the user–system dialogue evolution and to assess that the system recognizes both lower and upper bounds predicted by human experts.

The system's questions are preceded by the identification QL-CONST1:. Requests for user inputs are preceded by the word User:. Information supplied by the user is printed in bold. Author's explanations (when necessary) about dialogue progress are placed in parentheses. Because of space limitations, we summarize the displayed dialogues by suppressing some questions which will not affect the understanding of the system performance.

The first example assumes the existence of a hypothetical concrete structure whose construction process was assumed to follow optimal and high quality guidelines. Visual inspection was assumed to give excellent results, i.e., no cracks, honeycombs, bad surface finishes or reinforcement without cover were observed. The following text reproduces the messages and dialogue that will take place between the user and the computer:

OPTIONS MENU: Turn the WHEEL and select OPTION

1... LOAD the Knowledge Base
2... LOAD the Evidences Base
3... RUN the Expert
4... LIST a priori and updated probabilities
5... LIST conditional probabilities
6... EXIT the Expert

This menu is recursively called, allowing the user to select the desired actions. When the selected option is 3, the system starts its consultation process.

Please answer questions with integer numbers as indicated in the scale below .....

−5	0	+5
NO	absolute uncertainty	YES

Then I will try to give a reasonable prediction about the quality level of your structure ...

— START of Dialog —

QL-CONST1: What about control of CONCRETE QUALITY?
Were there enough compression strength tests on cylinders ?

User: 5

QL-CONST1: Were there any COLUMNS outside their vertical lines ?
User: −5
QL-CONST1: Were any FLEXURE CRACKS observed ?
User: −5
QL-CONST1: Were there any reinforcement bars without COVER ?
User: −5
QL-CONST1 : Were any SHEAR CRACKS in beams observed ?
User: −5

(As the dialogue progresses, the system incorporates more and more *a posteriori* information and, finally, after a few more questions, it announces the end of the dialogue and its most likely conclusion.)

QL-CONST1: Were there qualified PERSONNEL to place the FORMWORK and to remove them?
User: 5
QL-CONST1 : Were there qualified PERSONNEL to
handle and place the reinforcement ?
User: 5
QL-CONST1: Were there any previous studies on SOIL BEHAVIOUR ?
User: 5

—— END of Dialog ——

My PREDICTION is: The structure has GOOD quality level with a probability of 95%

Do you wish to ask me any other question (Y/N ... ?
Yes

If the answer if Yes the system proceeds to start a new dialogue. If the answer is No the system returns the control to the user at the main menu. Although the system prints only the most likely conclusion with its associated probability, the user could obtain all the probability values (*a priori*, updated and conditional) by simply selecting options 4 or 5 in the main menu.

The second example presented here assumes the existence of a hypothetical poorly built concrete structure having no detailed plans and no qualified personnel and erected without any proper control over the materials quality and strength. As might be expected from the situation depicted above, the required visual inspection is assumed to reveal a very calamitous structure showing a lot of cracked zones, honeycombs and non-homogeneous (geometrically speaking) structural components. Of course, this is a limit situation not normally observed in professional engineering practice. It is used here for demonstration purposes only.

The following text illustrates the conversation with the system for the evaluation of the hypothetical structure described above:

Please, answer questions with integer numbers as indicated in the scale below .....

−5	0	+5
NO	absolute uncertainty	YES

Then, I will try to give a reasonable prediction about the quality level of your structure ...

—— START of Dialog ——

QL-CONST1: What about control of CONCRETE QUALITY ?
Were there enough compression strength tests on cylinders ?
User: −5
QL-CONST1: Were any FLEXURE CRACKS observed ?
User: 5
QL-CONST1: Were there qualified DIRECTORS and competent INSPECTORS to control the construction process ?
User: −5
QL-CONST1: Were there any reinforcement bars outside their normal position ?
User: 5
QL-CONST1: Was there a good control of the REINFORCEMENT?
User: −5

(After some more questions, the system reaches its conclusion ...)

QL-CONST1: Were any SHEAR CRACKS in beams observed ?
User: 5
QL-CONST1: Were there qualified PERSONNEL to place the FORMWORK and to remove them ?
User: −5
QL-CONST1: Were there qualified PERSONNEL to handle and place the reinforcement ?
User: −5

—— END of Dialog ——

My PREDICTION is: The structure has POOR quality level with a probability of 97%

Do you wish to ask me any other question (Y/N) ... ? No

Good bye .... END of QL-CONST1

The preceding examples show that the system is able to recognize some of the limits for this specific knowledge field. However, in order to assess the system reliability, it becomes necessary to demonstrate that the expert system responses do not jump around local intermediate situations. Moreover, the system performance should be contrasted with that of a human expert and the degree of agreement evaluated.

Figures 3–7 are presented to this end. They show that the system behaviour is stable, if not always consistent. The set of evidence included in this version of QL-CONST was divided into two main groups, namely:

Evidence related to knowledge about the construction process, including plans, details, materials control, presence of qualified personnel, etc. This evidence group will be called KDC.

Evidence related to visual inspection results, which will be identified as VIR.

Thus, for instance *Figure 3* illustrates the system responses when KDC = −5, i.e., all questions in the KDC group were answered in such a way as to lead to the most unfavourable way for GOOD quality structures.

The vertical scale in *Figures 3–7* reflects the probability values (in percent) for the occurrence of each of the hypotheses considered. The horizontal scale contains the VIR values given for all questions related with evidences belonging to VIR group. It is appropriate to point out here that, obviously, all evidence may not have the same importance in the Bayesian inference process; on the contrary, they usually have different weight, probabilistically speaking. Nevertheless, for comparative purposes, this factor is not important.

Returning to *Figures 3–7*, remember that the system response is the largest final probability value and its associated hypothesis. For instance, in *Figure 3* when (KDC = −5) VIR = −2 the system prediction was a POOR quality level with a probability of 89 %.

Figure 3 represents the quality level QL for a subset of structures with KDC = −5 or, in other words, those structures whose construction process is known with absolute certainty to have followed the worst possible guidelines. Hence, as expected, the QL for such structures could never be GOOD and the system recognizes this fact. *Figure 3* shows the variation of $P(H:E)$ as the quality of the VIR ranges from −5 (bad) to +5 (good). Observe that, even in the presence of more or less satisfactory VIR

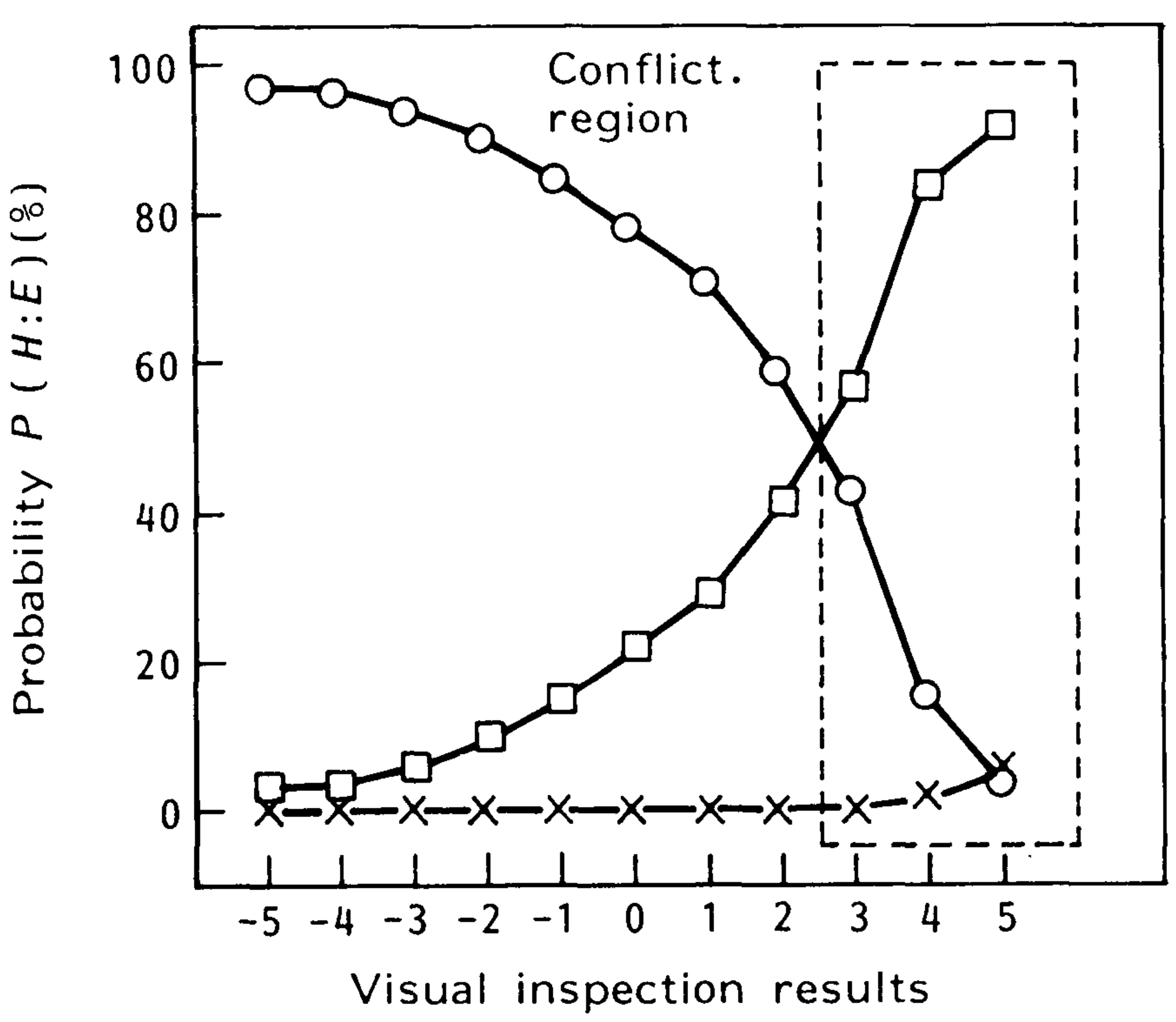

Fig 3 Expert system responses for KDC = −5 key: (×) GOOD; (□) MEDIUM; (○) POOR

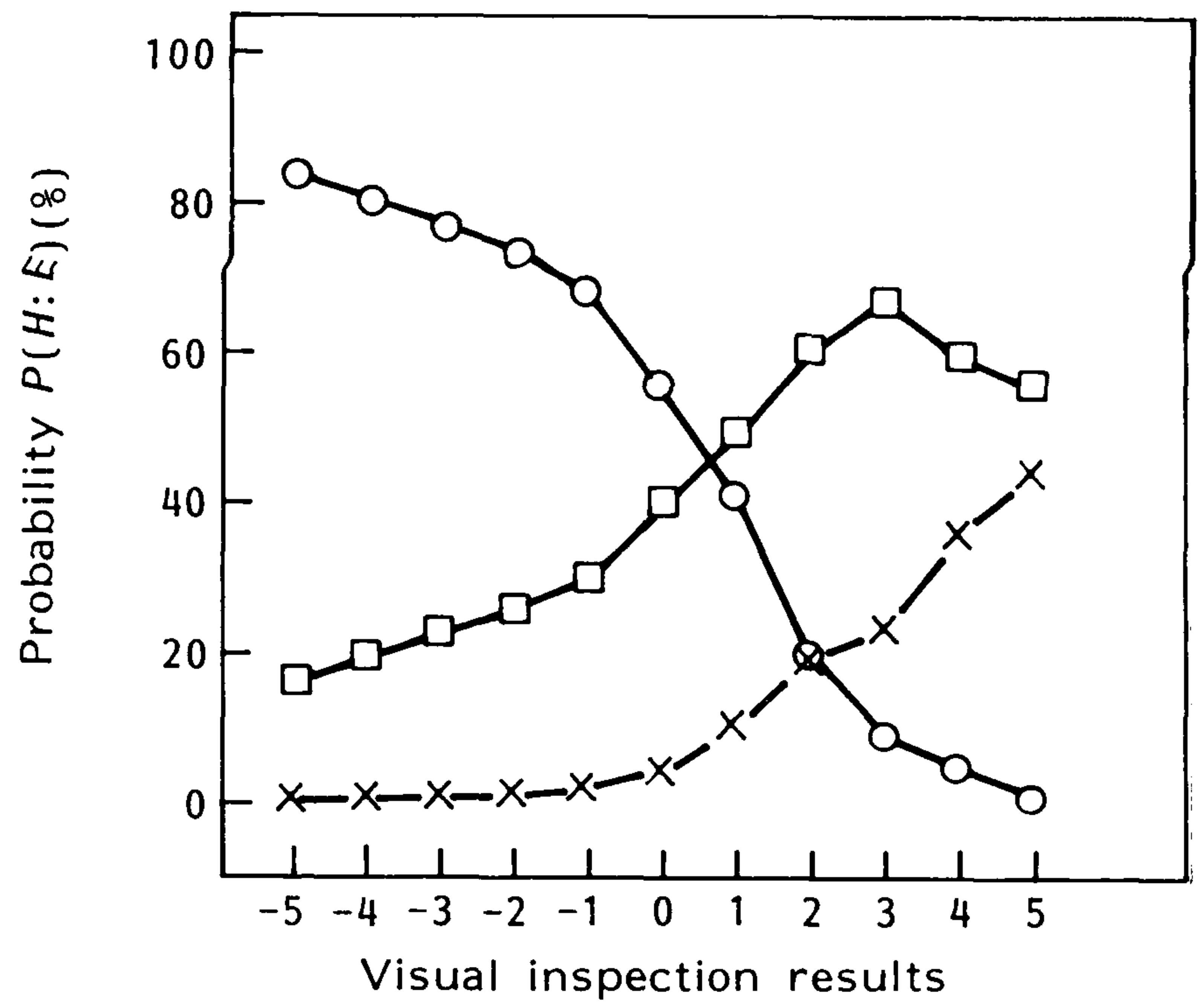

Fig 4 Expert system responses for KDC = −2 (key as in Figure 3)

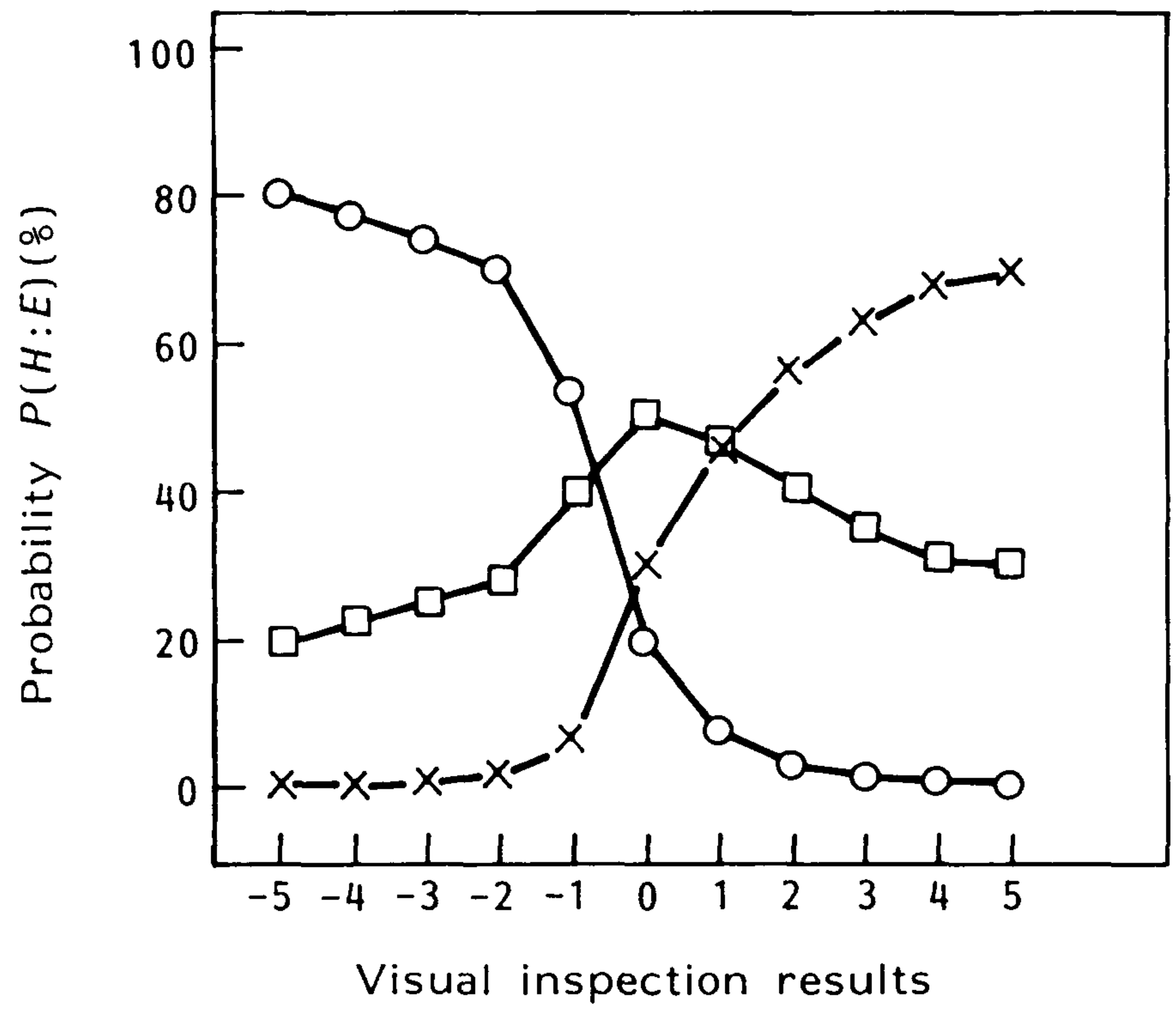

Fig 5 Expert system responses for KDC = 0 (key as in Figure 3)

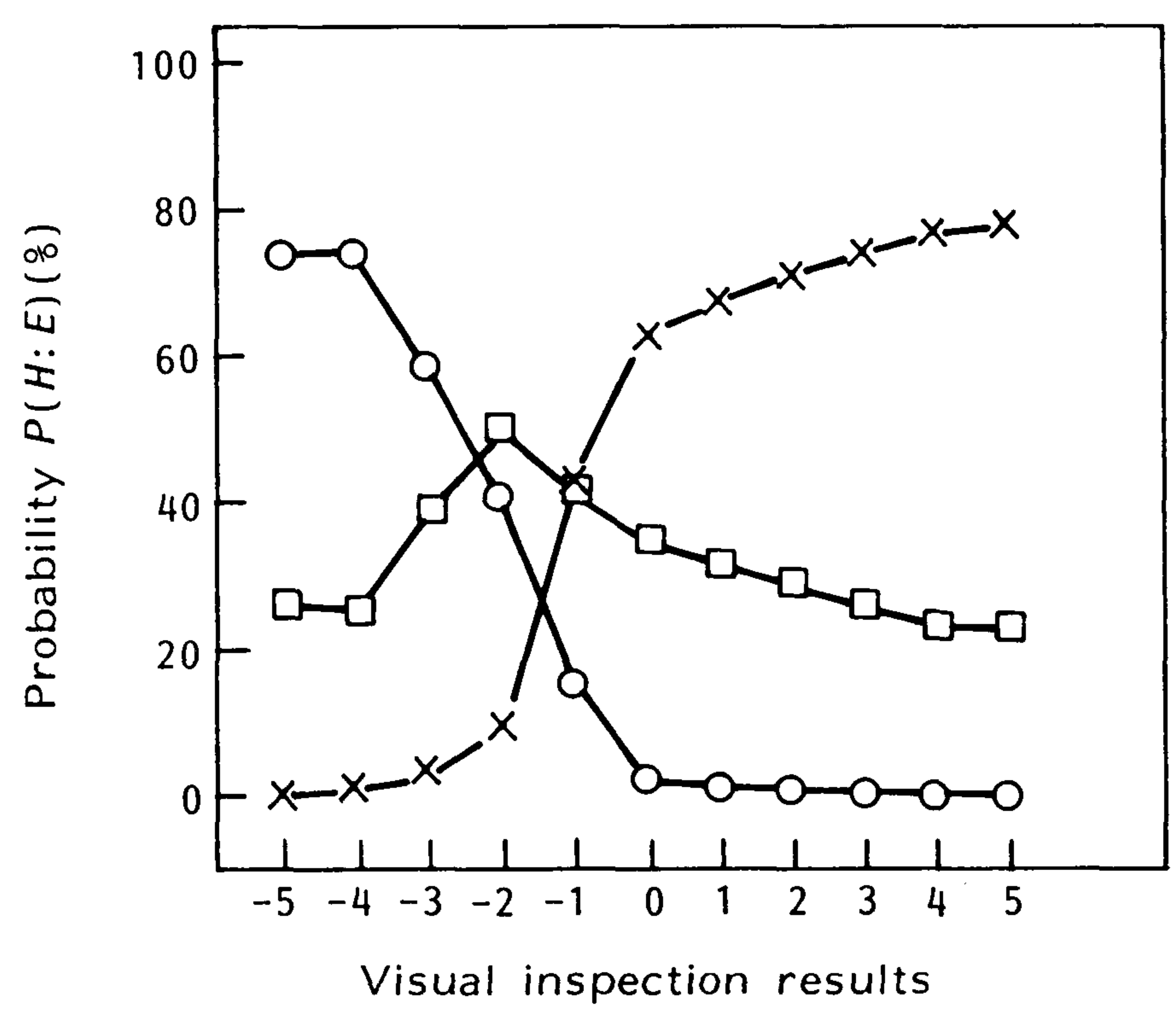

Fig 6 Expert system responses for KDC = 2 (key as in Figure 3)

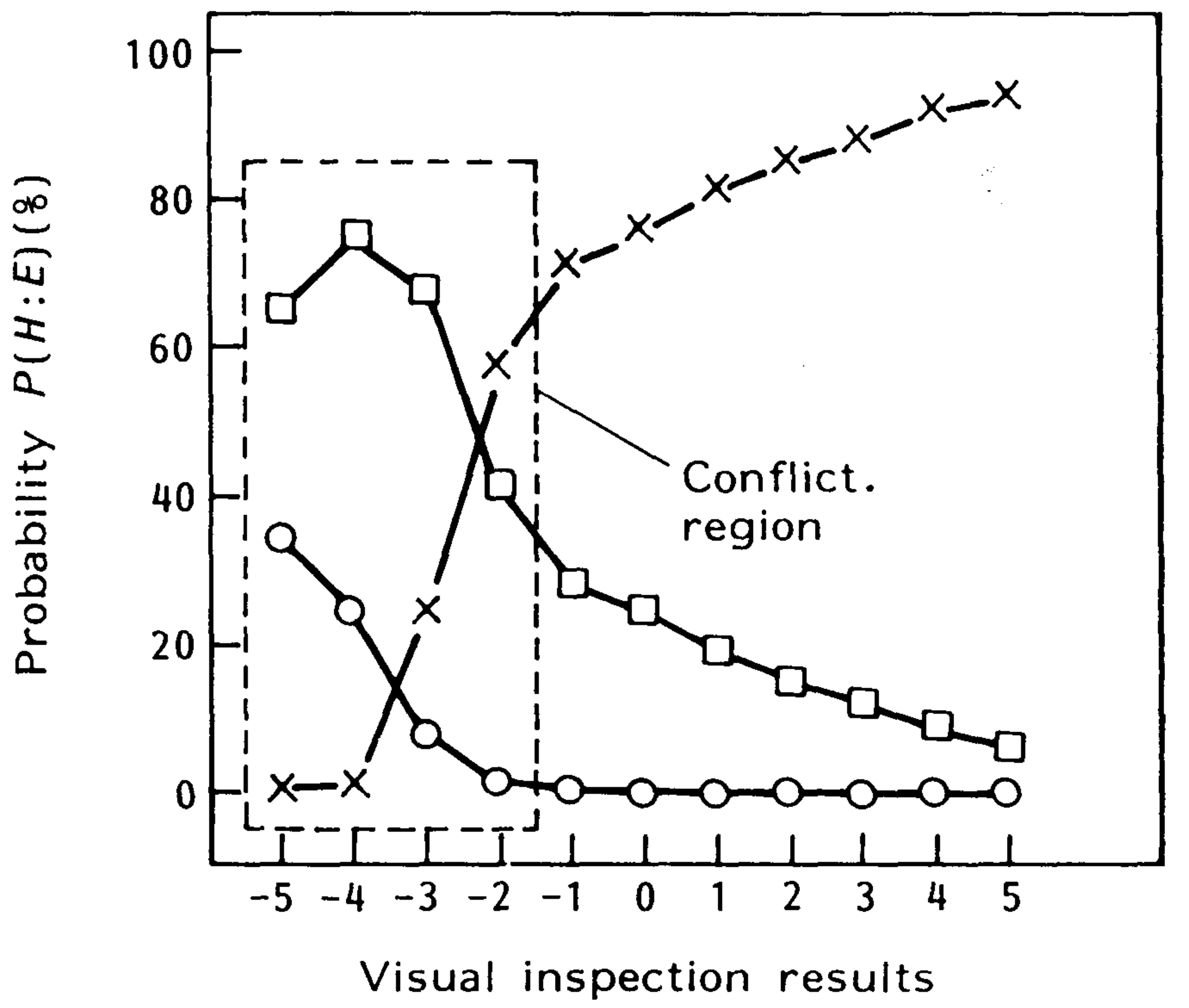

Fig 7 Expert systems responses for KDC = 5 (key as in Figure 3)

values (say, until VIR = 2) the system assigns the *poor* grade, which could be seen as a conservative criterion. For VIR values larger than 2, the system recognizes a real-world piece of nonsense identified as a conflictive region in the figure. Normally it is improbable that poor construction processes could give acceptable QL structures.

Figure 4 (KDC = −2) contains the QL results for those structures whose construction process is deemed to be more or less bad. Observe again the conservative criterion exhibited by the system: it assigns the *medium* grade, even in the presence of either good or excellent VIR values although there is an increase in the *Good* grade probability value.

Figure 5 (KDC = 0) illustrates the QL results for an absolute uncertainty about the construction process, i.e., where there is no information on available. As expected, the VIR parameter is decisive in evaluating the QL, except in the VIR = 0 case. However, such a case is an improbable one: no one would be able to give any prediction about structural QL having no knowledge of the construction process without making any visual examination of it. *Figure 6* (KDC = 2) shows the QL results when there is a moderate confidence in a suitable construction process. As expected, the VIR parameter is again decisive.

Finally, *Figure 7* (KDC = 5) contains the QL results for absolute certainty in a suitable construction process. Once again, as with *Figure 3*, the system recognizes a real-world contradiction: it is not normally probable that well-built structures could exhibit either bad or calamitous final aspect. These real-world nonsense situations are grouped together with a dashed line inside the conflictive region in the figure. As can be observed from *Figure 3–7*, $P(H:E)$ varies smoothly with the change in confidence of the evidence.

From another point of view, satisfactory results were obtained, when comparing the system's judgement to that of a human expert. In most cases, human experts did not hesitate to claim that they agreed with the tenor of the answers given by the system. This aspect offers some encouragement for improvement of the system by adding more probability based rules and introducing more refined gradation in the set of hypotheses considered.

Conclusions

A knowledge based system prototype for quality level prediction in concrete structures has been presented. The knowledge base developed here for dealing with structural quality assessment was extensively tested through a number of example cases. It has shown a satisfactory performance even in the presence of limit situations.

Acknowledgements

This work was carried out under grant No. 1306–86 of the Comision Asesora de Investigacion Cientifica y Tecnica (CAICYT) of the Spanish Ministry of Education and Science (MEC). The authors also express their thanks for the support of the Consejo de Desarrollo Cientifico y Humanistico (CDCH) of the Central University of Venezuela.